University of Michigan Medical School

State-Of-The-Art of Current PET-AS Algorithms and Their Advantages and Limitations for Clinical Application

Issam El Naqa, PhD, DABR

The Department of Radiation Oncology
University of Michigan

University of Michigan Medical School

Acknowledgements

Task Group Report

Classification and evaluation strategies of auto-segmentation approaches for PET: Report of AAPM task group No. 211

Mathieu Hatt, John A. Lee, Charles R. Schmidtlein, Issam El Naqa, Curtis Caldwell, Elisabetta De Bernardi, Wei Lu, Shiva Das, Xavier Geets, Vincent Gregoire, Robert Jeraj, Michael P. MacManus, Osama R. Mawlawi, Ursula Nestle, Andrei B. Pugachev, Heiko Schöder, Tony Shepherd, Emiliano Spezi, Dimitris Visvikis, Habib Zaidi, Assen S. Kirov

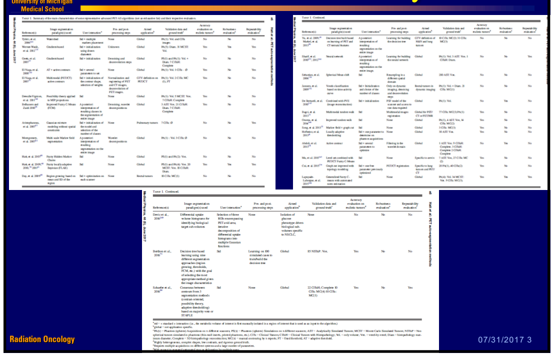
Toward a standard for the evaluation of PET-Auto-Segmentation methods following the recommendations of AAPM task group No. 211: Requirements and implementation

Beatrice Berthon, Emiliano Spezi, Paulina Galavis, Tony Shepherd, Aditya Apte, Mathieu Hatt, Hadi Fayad, Elisabetta De Bernardi, Chiara D. Soffientini, C. Ross Schmidtlein, Issam El Naqa, Robert Jeraj, Wei Lu, Shiva Das, Habib Zaidi, Osama R. Mawlawi, Dimitris Visvikis, John A. Lee, Assen S. Kirov

Radiation Oncology /31/2017 2

University of Michigan Medical School

TG-211 PET-AS Summary



Radiation Oncology 07/31/2017 3

Classification of PET-AS

- Use of pre- and post-processing steps
- Level of automation
- Segmentation/image processing algorithm employed and its assumptions and complexity

Radiation Oncology 07/31/2017 4

Classes of PET-AS based on Algorithm

- Fixed and adaptive threshold algorithms
- Advanced algorithms
  - Gradient-based segmentation
  - Region growing and adaptive region growing
  - Statistical-based approaches
  - Learning and texture-based segmentation
- Combined with image processing and/or

Reconstruction

- Segmentation of multimodality images

Radiation Oncology 07/31/2017 5

Thresholding algorithms I

- Thresholding is expressed as follows (after images are converted to SUV):

$$\hat{I} \in \Upsilon_T(I_i) = \begin{cases} 1, I_i \geq T, \\ 0, I_i < T, \end{cases} \quad I_i \in I_{VOI}$$

where $\Upsilon_T(.)$ the indicator function for threshold T

- *T* could be fixed or adapted

Radiation Oncology 07/31/2017 6

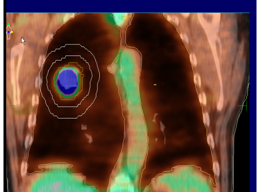
Thresholding algorithms II

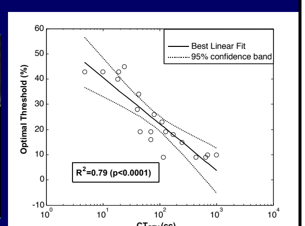
University of Michigan Medical School

Comments	Threshold Estimator
Drever, et al.'s single-parameter FTS fit[257]: It is most notable for its use of the histogram's mode for more stable estimation of the background.	$T = a\left(I_{max} - I_{bkg}\right) + I_{bkg}$
Nestle, et al.'s single-parameter FTS fit[23]: This fit uses the mean of voxels greater than 70% of the lesion's maximum. The use of the mean instead of the maximum uptake reduces the variability.	$T = a\ I_{mean,70\%max} + I_{bkg}$
Daisne, et al.'s show a two-parameter FTS fit model[137]: The scaling parameter, I_{max}, can be recast as a mean-value or volume-based measure for an ATS algorithm.[258]	$T = a + b\frac{I_{bkg}}{I_{max}}$
Schaefer, et al.'s two-parameter FTS fit[30]: This fit is extended from Nestle's scheme above.[23]	$T = \frac{a\ I_{mean,70\%max} + b\ I_{bkg}}{I_{max}}$
Erdi, et al.'s two-parameter FTS fit[48]. It was noted that a fixed threshold of 42% worked well for large lung tumors, however, the authors go on to say that its use should be limited to homogeneous uptake distributions.	$T = a\ e^{-bV(T)}$
Black, et al.'s two-parameter ATS fit[53]: The use of the mean SUV to make the algorithm more stable to noise requires a threshold for its calculation.	$T = a + b\ I_{mean}\left(V\left(T\right)\right)$
Biehl, et al.'s two-parameter ATS fit[46]: The volume is the GTV defined by CT. This algorithm was shown to work for a range of tumor volumes in NSCLC.	$T = I_{max}\left(a + b\ ln\left(CT_{GTV}\right)\right)$
Jentzen, et al.'s three-parameter ATS fit[51]: The parameters were fitted from phantom data. The volume parameter requires a threshold.	$T = \frac{a}{V(T)} + b\frac{I_{bkg}}{I_{max}} + c$
Nehmeh, et al.'s four-parameter ATS fit[52]: The fit used Monte Carlo simulation results to avoid cold wall effects.	$T = I_{max}\left(a + b\ V^{c}(T)e^{d/v(T)}\right)$
Burger, et al.'s Background Subtracted Lesion (BSL)[259]: Not meant as segmentation but rather a volume estimation scheme, an equivalent volume threshold can be found (Li et al.[260]) Note that this method tends to overestimate the volume by including spill-out.	Procedure: T, such that the volume from this threshold matches the BSL volume derived from histogram analysis

Adaptive thresholding example

University of Michigan Medical School





Biehl et al., JNM, 2006

Thresholding algorithms III

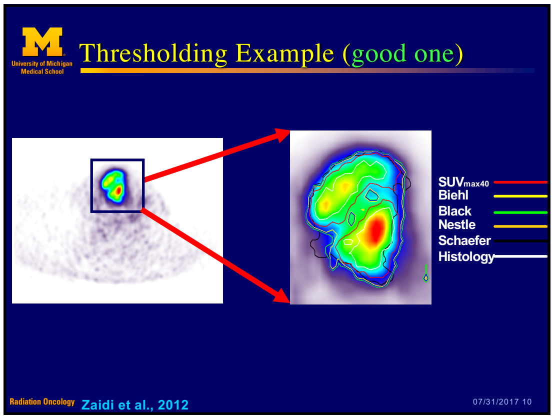
University of Michigan Medical School

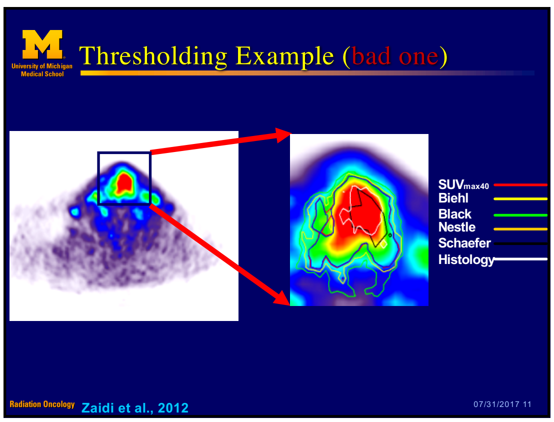
Pros

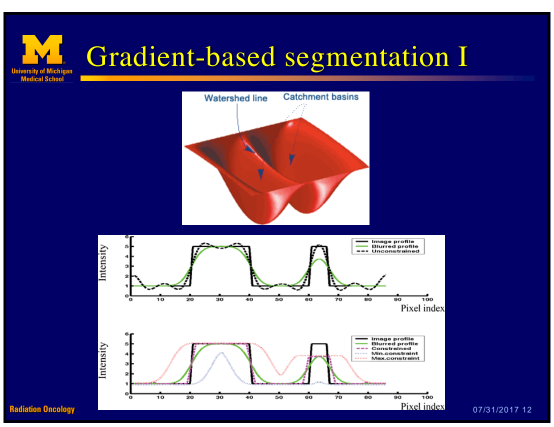
- Simple
- Easy to implement

Cons

- Assumes well defined object boundary and uniform background
- Sensitive to imaging acquisition parameters (resolution, contrast, noise)


University of Michigan Medical School
Thresholding Example (good one)
SUVmax40
Biehl
Black
Nestle
Schaefer
Histology
Radiation Oncology
Zaidi et al., 2012
07/31/2017 10


University of Michigan Medical School
Thresholding Example (bad one)
SUVmax40
Biehl
Black
Nestle
Schaefer
Histology
Radiation Oncology
Zaidi et al., 2012
07/31/2017 11


University of Michigan Medical School
Gradient-based segmentation I
Watershed line
Catchment basins
Intensity
Pixel index
Radiation Oncology
07/31/2017 12

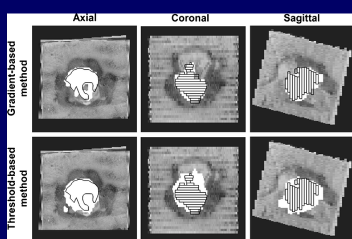
Gradient-based segmentation II

Pros
- Efficient
- Easy to implement

Cons
- Sensitive to imaging acquisition parameters (resolution, contrast, noise)
- Requires pre-processing (denoising/deblurring

Radiation Oncology 07/31/2017 13

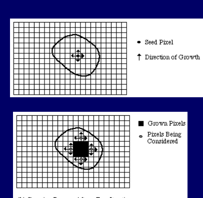
Gradient-based segmentation III



Radiation Oncology Geets et al., 2007 07/31/2017 14

Region growing and adaptive region growing I

- Generally,
  1) Start by a voxel (seed)
  2) Check neighboring voxels and add them if they are similar to seed
  3) Repeat (2) until no voxel can be added



Radiation Oncology 07/31/2017 15

Region growing and adaptive region growing II

Pros

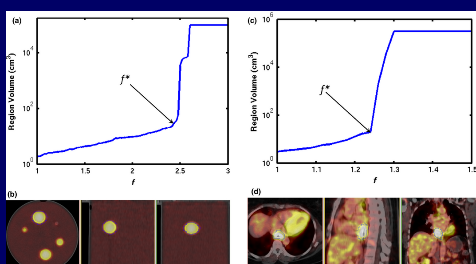
- Efficient
- Easy to implement

Cons

- Sensitive to seed selection (initialization)
- Adaptation criteria can vary by application

Radiation Oncology 07/31/2017 16

Region growing and adaptive region growing III



Radiation Oncology Hatt et al., 2017 07/31/2017 17

Statistical

- **Bayes rule**

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

- **Fuzzy Locally Adaptive Bayesian (FLAB)**

$$d^q(c|y_t) = \frac{p_{t,c}^{q-1} f^{q-1}(y_t|c)}{p_{t,0}^{q-1} f^{q-1}(y_t|0) + p_{t,1}^{q-1} f^{q-1}(y_t|1) + \left(1 - p_{t,0}^{q-1} - p_{t,1}^{q-1}\right) \int_0^1 f^{q-1}(y_t|\theta)d\theta}$$

Where *d* is posterior distribution with respect to class *c* a given voxel *t*; *f* is probability density distribution (Pearson system) and *p* is prior probability

Radiation Oncology Hatt et al., 2009 07/31/2017 18

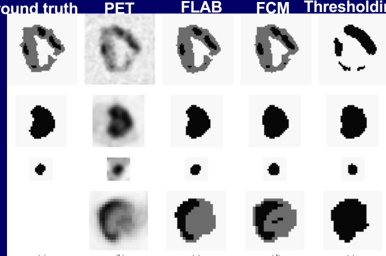
Statistical II

Pros
- Robust
- Flexible
- Incorporate prior knowledge (Bayesian)
- Can perform well with heterogeneous uptake distributions

Cons
- More complex
- May require statistical knowledge
- Iterative (slow convergence)

Radiation Oncology 07/31/2017 19

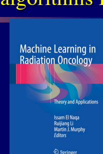
Statistical III



Radiation Oncology Hatt et al., 2010 07/31/2017 20

Learning and texture-based segmentation algorithms I

- Applies machine learning techniques
  - Supervised (NN, SVM, decision trees, Random forests, etc)
  - Unsupervised (PCA, clustering (FCM, K-means, etc)
- Could be feature-based or voxel-based



Radiation Oncology 07/31/2017 21

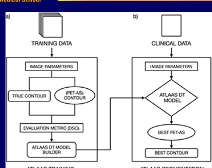
Learning and texture-based segmentation algorithms II

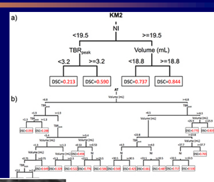
Pros
- Robust
- Accurate
- Can perform well with heterogeneous uptake distributions

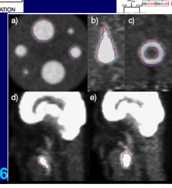
Cons
- May require training (supervised)
  - Needs ground truth (teacher)
  - Time consuming
- Risk of overfitting
- May depend on extracted features or selected parameters

Radiation Oncology 07/31/2017 22

Learning and texture-based segmentation algorithms III

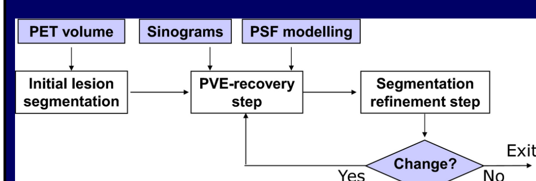




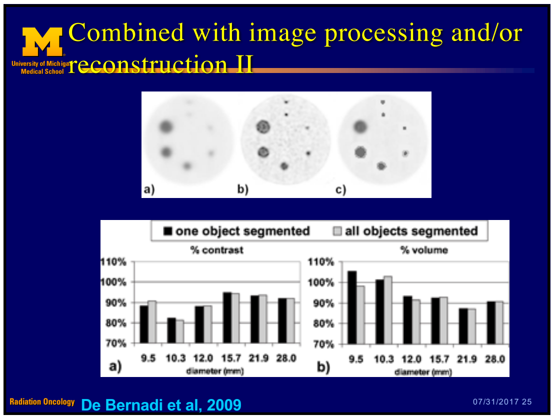


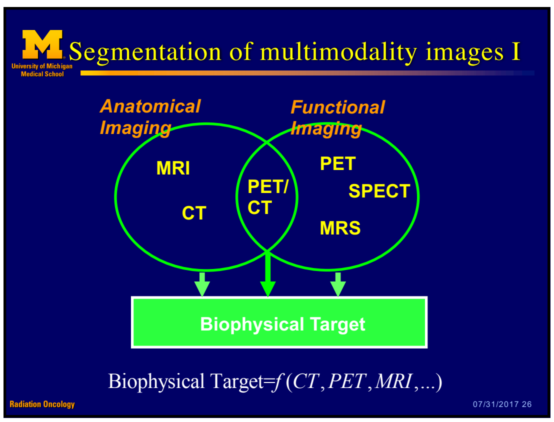
Radiation Oncology Berthon et al, 2016 07/31/2017 23

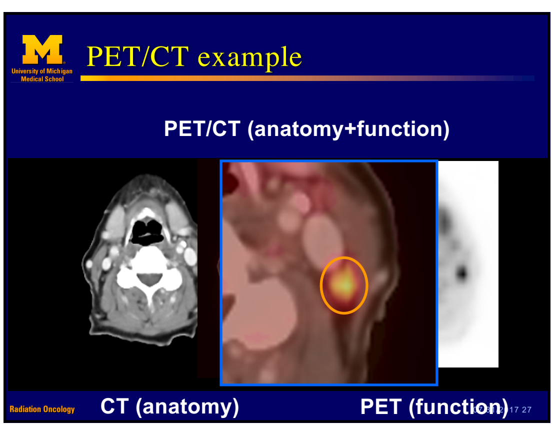
Combined with image processing and/or reconstruction I

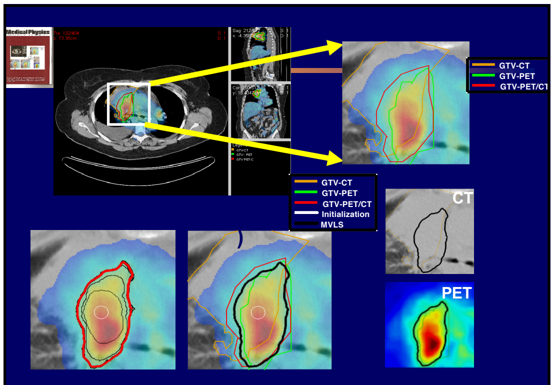


Radiation Oncology De Bernadi et al, 2009 07/31/2017 24


Combined with image processing and/or reconstruction II
University of Michigan Medical School
a)
b)
c)
one object segmented
all objects segmented
% contrast
% volume
110%
100%
90%
80%
70%
9.5 10.3 12.0 15.7 21.9 28.0
diameter (mm)
Radiation Oncology
De Bernadi et al, 2009
07/31/2017 25


Segmentation of multimodality images I
University of Michigan Medical School
Anatomical Imaging
Functional Imaging
MRI
CT
PET/CT
PET
SPECT
MRS
Biophysical Target
Biophysical Target=f (CT, PET, MRI,...)
Radiation Oncology
07/31/2017 26


PET/CT example
University of Michigan Medical School
PET/CT (anatomy+function)
CT (anatomy)
PET (function)
Radiation Oncology



Radiation Oncology   El Naqa et al, Med Phys, '07   07/31/2017 28

Summary of automated lesion detection in PET

Category	Characteristics	Limitations
Thresholding techniques	Most frequently used due to their simple implementation and high efficiency.	Hard decision-making. Too sensitive to PVE, tumour heterogeneity, and motion artefacts. Some methods focus on volume, others focus on intensity differences. Combination of both seems to provide best results [81].
Variational approaches	Subpixel accuracy, boundary continuity, and relatively efficient. They are mathematically well developed and allow for incorporation of priors such as shape.	Sensitive to image noise. As a PDE, stability and convergence could be subject to numerical fluctuations, especially if the parameters are not properly selected.
Learning methods	Utilize pattern recognition power. Two main types: supervised (classification) and unsupervised (clustering)	Computational complexity especially in supervised methods, which require time consuming training. Feature selection beside commonly used intensity is a flexibility but can also be a challenge.
Stochastic models	Exploit statistical differences between tumour uptake and surrounding tissues. Most natural to deal with the noisy nature of PET.	Effect of initialization and convergence to local optimal solutions are concerns, especially when compromises are made to improve efficiency.

Zaidi & El Naqa, Eur J. Nuc Med, 2010.

Radiation Oncology   07/31/2017 29

Conclusions

- Different PET-AS algorithms have their own pros/cons and selection of 'best' one is a compromise and a matter of convenience
- Most PET-AS algorithms are not commercially available software

Radiation Oncology   07/31/2017 30